Deep Learning for Automated Quantification of Tumor Phenotypes

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Computed Tomography II - Imaging Scientific Session
AAPM 2018 - Wednesday, 8/1/2018 10:15 AM - 12:15 PM
Changes in the Leading Cause of Death: Recent Patterns in Heart Disease and Cancer Mortality

Lung Cancer Staging

Classifications

Primary Tumor (T) Classification

- **TX**: Primary tumor cannot be assessed, or tumor proven by the presence of malignant cells in sputum or bronchial washings but not visualized by imaging or bronchoscopy.
- **T0**: No evidence of primary tumor.
- **T1a**: Tumor 3 cm or less in greatest dimension, surrounded by lung or visceral pleura without bronchoscopic evidence of invasion more proximal than the lobar bronchus.
- **T1b**: Tumor 2 cm or less in greatest dimension.
- **T2a**: Tumor more than 2 cm but 5 cm or less in greatest dimension.
- **T2b**: Tumor more than 2 cm but 7 cm or less in greatest dimension.
- **T3**: Tumor more than 7 cm or one that directly invades any of the following: parietal pleural (PLP), chest wall (including superior sulcus tumor), diaphragm, phrenic nerve, mediastinal pleura, parietal pericardium, or tumor in the main bronchus less than 2 cm distal to the carina but without involvement of the carina or associated atelectasis or obstructive pneumonitis of the entire lung or separate tumor nodule(s) in the same lobe.
- **T4**: Tumor of any size that invades any of the following: mediastinum, heart, great vessels, trachea, recurrent laryngeal nerve, esophagus, vertebra, rib, carina, separate tumor nodule(s) in a different (opposite) lobe.

Distant Metastasis (M) Classification

- **M0**: No distant metastasis.
- **M1**: Distant metastasis.
- **M1a**: Separate tumor nodule(s) in a central or peripheral lobe, or tumor with pleural nodule(s) or malignant pleural or pericardial effusion.
- **M1b**: Distant metastasis in a metastatic organ.

https://cancerstaging.org/references-tools/quickreferences/Pages/default.aspx
Artificial Intelligence Methods in Medical Imaging

Ahmed Hosny, Chintan Parmar, John Quackenbush, Lawrence H Schwartz and Hugo JWL Aerts

Artificial Intelligence in Radiology
Nature Reviews Cancer - 2018
Artificial Intelligence Methods in Medical Imaging

a Predefined engineered features + traditional machine learning

Feature engineering

Histogram

Texture

Expert knowledge

Shape

Selection

Classification

b Deep learning

Input

Hidden layers

Increasingly higher-level features

Output

Convolution layers for feature map extraction

Pooling layers for feature aggregation

Fully connected layers for classification

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Analytical Setup

**DISCOVERY**

RADIOThERAPY
- HarvardRT, n=317 (293)
- Radboud, n=147 (104)

SURGERY
- Moffitt, n=200 (183)
- MUMC, n=90 (88)

**TEST**

- Maastro, n=307 (211)
- M-SPORE, n=101 (97)

Performance was benchmarked against models based on the following features:
- clinical
- engineered
- volume
- diameter

Stability was assessed in the following scenarios:
- n=32 test/retest
- variance

Important regions were highlighted using activation mapping:
- activations

Biological basis was defined using genomic associations:
- genomics
Prognostic Signal

**Radiotherapy**

A. ROC-AUC

- AUC = 0.70
- n = 277
- p = 0.0001

B. KM survival curve

- m = 207
- p = 0.0001

**Surgery**

C. ROC-AUC

- AUC = 0.71
- n = 277
- p = 0.0004

D. KM survival curve

- m = 101
- p = 0.003
Benchmarking

- **RADIOTherapy**
  - **DEEP LEARNING**: 0.70
  - **CLINICAL**: 0.55
  - **ENGINEERED FEATURES**: 0.66
  - **VOLUME**: 0.64
  - **MAXIMUM DIAMETER**: 0.63

- **Surgery**
  - **DEEP LEARNING**: 0.71
  - **CLINICAL**: 0.58
  - **ENGINEERED FEATURES**: 0.58
  - **VOLUME**: 0.51
  - **MAXIMUM DIAMETER**: 0.50

> significantly worse than deep learning

* significantly better than random permutation
Input Stability

A) Prognostic stability with translation variance

B) Prognostic stability with translation variance

μ=0.68, σ=0.014

50 simulation runs
Evaluating Variability in Tumor Measurements from Same-day Repeat CT Scans of Patients with Non–Small Cell Lung Cancer
Evaluating the Prognostic Value of Tumor-Surrounding Tissue

[ROC-AUC plot with three panels showing AUC values of 0.63, 0.66, and 0.70 for DEEP-MAKSED, ENGINEERED, and DEEP-UNMAKSED models, respectively.]
## Activation Mapping

<table>
<thead>
<tr>
<th>INPUT IMAGE WITH ANNOTATIONS</th>
<th>ACTIVATION HEATMAPS</th>
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<tbody>
<tr>
<td><img src="image1.png" alt="Input Image 1" /></td>
<td><img src="heatmap1.png" alt="Activation Heatmap 1" /></td>
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<tr>
<td><img src="image2.png" alt="Input Image 2" /></td>
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